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Writer Identification with Hybrid Model using Hybrid HMM and ANN

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Abstract— In this paper, writer identification is performed with three models, namely, HMMBW, HMMMLP and HMMCNN. The features are extracted from the HMM and are classified using Baum Welch algorithm (BW), Multi layer perceptron (MLP) model and Convolutional neural network (CNN) model. A dataset, namely, VTU-WRITER dataset is created for the experiential purpose and the performance of the models were tested. The test train ratio was varied to derive its relation to accuracy. Also the number of states was varied to determine the optimum number of states to be considered in the HMM model. Finally the performance of all the three models is compared.

Keywords :Convolutional neural network (CNN) model ,Hidden markov models, Multi layer perceptron (MLP) model , Writer identification.

I. INTRODUCTION

The word biometrics is a Greek word meaning life (bio) and measurement (metric). The measurement of life means measuring the physical characteristic from a subject that has life. Examples of biometric include collecting the finger prints, iris, blood sample or hair for DNA, geometries of hand or fingers etc. These factors are associated with some shape or characteristic of the person's body. These types of biometrics that can be collected from the human body can be termed as physiological biometrics. There are also other types of biometrics that are behavioral in nature. That means, the behavior of each person can be characterized separately and that information can be used to identify the person. These biometrics are not part of the person's body, it belongs thuman behavior. Examples of behavioral biometrics include signature, handwritten text, key strokes, voice etc. The physiological and behavioral biometrics has its own advantages and limitations. For example, the physiological biometrics cannot be modified by a person though it belongs him, whereas the behavioral biometrics can be modified by force or practice by a person. Also the behavioral biometrics change with time and hence it is dynamic in nature [1-3].

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Two decades back, finger prints used to be collected with ink and paper for property registrations, investigations by law enforcement agencies, or as signatures by people who cannot sign on paper. The same process of collecting the finger prints are automated now. The finger prints are unique to every person and the pattern does not change with time [7-9].

The finger prints are different among different fingers of same hand and similar fingers of other hand of the same person. It also differs from person to person though the persons are siblings are twins. Patterns in the finger print are formed by ridges and furrows. Ridge patterns never change in life time and this principle is known as immutability. Similarly non-commonality of finger prints between persons is known as uniqueness. Face recognition has been the research topic not only in the field of engineering but also in the fields of neurosciences, psychology, optics and machine learning [10]. This method has some advantages over the finger print method since this is a non-invasive method. It does not require person acceptance to provide the image for identification. Iris is the thin elastic tissue in the eye. Iris controls the amount of light that enters into the eye by controlling the size and diameter of pupil. During the young ages like childhood and teen ages, size of iris grows and it remains constant during rest of the life. Similar to finger prints, iris is unique to each person, including twins. The iris of left and right eyes is also different for a person. Signature by a person is very unique to identity of a person. Every person has his or her own style in writing the signature. Signature recognition falls under the category of behavioral biometric recognition. Pattern in signatures is captured in the training of the model. The way the signature is made is more important than how it appears. Signatures are characterized by not just the way signature is written, but also the speed, direction of stroke and pressure applied on the paper. There are some limitations in the signature recognition. The limitations have very high impact on the life of the the final paper but after the final submission to the journal, rectification is not possible. on the paper. There are some limitations in the signature recognition. The limitations have very high impact on the life of the person. For example, if the signatures are forged, it may lead to financial losses, property losses, crime related implications etc. While the writing style of the signature is an important character to recognize a person, exposing the signature is dangerous and hence many people do not like to share their signature to build the database. In order to address the limitations of signature recognition, another method can be used to capture the writing patterns of a person while not compromising on the exposing the signatures.

Handwriting any text on a paper or a tablet is an alternative to signature to capture the writing patterns of a person. It is again unique to a person. Handwritten scripts are collected for each person and a model can be trained to learn the patterns of different people. When a new handwritten text is presented to the model, it can recognize the person that script belongs to.

The handwriting recognition or identification is also known as automatic writer identification. The handwriting recognition can be classified into two major categories, namely, on-line and off-line [11-14]. As explained before, the on-line handwriting recording involve capturing dynamic characteristics like speed, pressure direction of stroke, number of pauses etc [15-17]. All this additional information along with the content of the text will make the online recognition more robust than the off-line method in which only content of text is considered in the feature set [18-19]. Traditional systems use the information that you have and biometric systems use the information that you are.

Apart from other methods [20-24], deep learning is another approach which can be used for writer identification. Convolutional neural network (CNN) is a one of the deep learning models that can be employed. AlexNet [25] is one of the important mile stones in the development of deep learning models, which is based on CNN. The CNN has also been used in document analysis [26-28]. The CNN application in the area of writer recognition is gaining popularity [29-32]. As discussed before, the analysis can be test dependent or text independent. The text dependent based writer identification features can be derived using CNN. Fiel and Sablatnig [29] has proposed the first writer identification algorithms using deep learning methods. CNN activation was used in this approach. The activations were extracted from the penultimate layer of the CNN.

II. HMMCNN ALGORITHM

A HMM is comprised of many states. A system under modeling is represented with finite number of states. The system will be in any one of the states at a given point of time. The number of states that system can exist depends on the physical nature of the system. When a system is in certain state, it is observable and hence it generates observations. The system hidden states may not be observable directly but the observations can be linked to each hidden state of the system. System undergoes transition from one state to any other state. The probabilities that a system changing from one state to any other state is represented in state transition matrix. Similarly, when a system is present in one state, many observations are possible. Hence there is also another matrix, namely, emission probability matrix that is specific to a system which describes the transition probabilities from a given state to observation. The generated observations have a statistical continuous or discrete distribution.

Assume that system can be in any one of the N states. Let Q be the set of states, then

$$Q = \{Q_1, Q_2, Q_3, \ldots\ldots Q_N\} \tag{1}$$

At a given time t, state of the system $q_t \in Q$

Each state has certain initial probability. For a system that has N states, $\Pi = \{\pi_1, \pi_2, \pi_3, \ldots\ldots \pi_N\}$ and $\pi_i = P(q_t = Q_i)$.

State transition probability matrix represents the probability of system moving from one state *i* to another state *j*, and hence the state transition probability matrix can be written as $A = \{a_{ij}\}$.

$$a_{ij} = P(q_t = Q_j \mid q_{t-1} = Q_i) \tag{2}$$

$$1 \le i \le N \; and \; 1 \le j \le N \tag{3}$$

$$\sum_{j=1}^{N} a_{ij} = 1 \;\; for \;\; 1 \le i \le N \tag{4}$$

Let the observation, at any given point of time, is O_t.

Every hidden state Q_t at any point of time t generates an observation O_t. The observation state O_t follows a continuous or discrete distribution. Every hidden state Q_t can generate many observation states O_t.

The emission probability matrix that represents the probabilities of system generating an observation state O_t from a hidden state Q_t is denoted by $B = \{b_j(O_t)\}$.

where

$$b_j(O_t) = P(O_t \mid q_t = S_j) \tag{5}$$

$b_j(O_t)$ is the probability of observation when the state of the system is at $q_t = S_j$,

If HMM represent a discrete system, with *M* observed states, then

$$V = \{V_1, V_2, V_3, \ldots\ldots V_M\} \tag{6}$$

$$a_{ij} = P(q_t = V_j \mid q_{t-1} = V_i) \tag{7}$$

$$b_j(k) = P(O_t \mid q_t = V_j), \quad 1 \le j \le N \tag{8}$$

If HMM represents a continuous distribution, then the observations O_t follow continuous probability distributions.

$$b_i(O_t) = \sum_{k=1}^{M_i} c_{ik} N(O_t, \mu_{ik}, \Sigma_{ik}), \quad 1 \le i \le N \tag{9}$$

where

$N(O_t, \mu_{ik}, \Sigma_{ik})$: Gaussian density function

μ_{ik} : Vectors of mean of states

Σ_{ik} : Matrix of Covariance of states

That is μ_{ik} and Σ_{ik} are dependent on the state *i*.

If these vectors are assumed to independent of the state, then

$$b_i(O_t) = \sum_{k=1}^{M_i} c_{ik} N(O_t, \mu_k, \Sigma_k), \quad 1 \le i \le N \tag{10}$$

Also (1.12)

$$N_t(O \mid \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma|^{\frac{1}{2}}} e\left[-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right] \tag{11}$$

Overall, the HMM can be denoted as

$$\Lambda = (A, B, \Pi) \quad (1.13) \tag{12}$$

The written text can be identified with a writer with the help of HMM. The written text by a writer can be divided into N states. Unlike face recognition, the text does not have a fixed set of states. For example in case of face recognition, the states can be defined as hair, forehead, eyes, nose, mouth and chin in the order from top to bottom in the face. This order is a natural order and hence they are less affected by the scaling or rotation effects.

But in case of hand written text, the states keep changing from text to text unless all writers write the same text. Also there will be variation in each character that each writer is writing even if the text remains same.

Each state is a block of size 50x50 and hence there are 2500 pixels. For a color image, there are three color channels and hence there are 7500 pixel intensities. Since the image is converted into a gray scale image, there are only 2500 pixel intensities. Since the block size is square in shape, each block can be solved for Eigen values directly. However, to develop a generic procedure irrespective of shape of each block, Singular Value Decomposition is implemented and three values of U(1,1), S(1,1) and S(2,2) are derived for each of the block. Hence there are a total of 910 x 3 = 2730 features for each text image.

The problem of huge number of weights in MLP models are addressed in the CNN. Reason for huge size of weight matrices are due to processing of one dimensional vector inputs. This problem is over come when the input is presented in two dimensional form and, then in subsequent layers also, neuron outputs are processed in two dimensional form. In a CNN, every neuron in the intermediate layers is connected with a region in the previous layer. Finally for classification purpose, the output in feature extraction layer is again concatenated into a single column vector and then fed to a fully connected layer. The output layer will have a have number of neurons equal to number of classes to be discriminated.

In this model, the image is divided into overlapping or non-overlapping blocks both horizontally or vertically. Fig. 6.3 shows the non-overlapping states or blocks that were created by dividing the text image both horizontally and vertically.

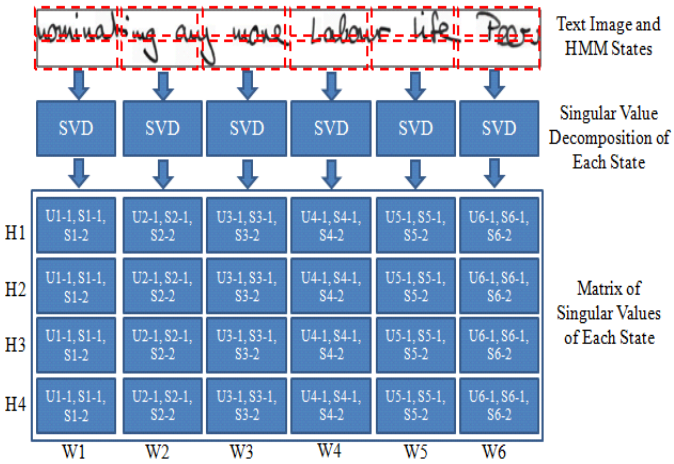

Fig. 1: Feature Extraction for Classification with CNN

There are 6 non-overlapping blocks in horizontal direction and 4 blocks in vertical direction, for example. Each block has pixel intensities of only one channel since the image is converted to gray scale image. Since each block may be rectangular in shape, singular value decomposition is applied to extract the Unm-1, Snm-1 and Snm-2 values, where *n* is the block number in horizontal direction and *m* is the block number in vertical direction. In this case, there is no concatenation of features from HMM is required at the input of CNN. The features from HMM can be input in two dimensional form to CNN.

Algorithm used in this research work is shown in Fig. 4.3 and is as follows:

1. Input the image and create the states of the image. Each state can be overlapping with other states.
2. For each state, pixel intensities are extracted in the form of a matrix. If it is a color image then there can be three matrices or a single matrix can be formed with concatenation.
3. Use singular value decomposition method to extract the singular values and Eigen vectors.
4. Store the first Eigen vector coefficient of left singular vector in a variable.
5. Store the singular values in a separate vector S.
6. Define the first feature as Eigen vector coefficient of left singular vector.
7. Define the second feature as first singular value stored in vector S.
8. Define the second feature as second singular value stored in vector S.
9. Now each state in the text image is defined by feature as Eigen vector coefficient of left singular vector, first and second singular values. Store the three features into a vector array or a cell.
10. Repeat steps 3 to 9 for each state.
11. Repeat steps 1 to 10 for all the images.
12. Concatenate all the features into two dimensional matrix.
13. Create train set and test set.
14. Define the number of convolutional layers with activation function as ReLU in CNN.
15. Define the number of Max pool layers with activation function as ReLU in CNN.
16. Define the number of hidden layers with activation function as ReLU in fully connected layers for classification.
17. Define the output layer with activation function as softmax in CNN.
18. Input the all the arrays of train set features extracted in step 13 to CNN for writer identification to train the CNN. Use minimization of cross entropy loss function as objective function.
19. Input the all the arrays of test set features to CNN for writer identification to test CNN.
20. Instead of CNN in the above steps, Baum Welch (HMMBW) and MLP are also run (HMMMLP) to compare the performances.

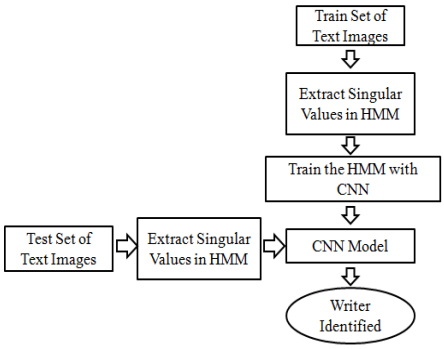

Fig. 2: Block diagram of proposed HMMCNN model with singular values as features

III. SIMULATION RESULTS

VTU-WRITER dataset has been created with the text written by 100 writers. Each of the sample images in both train and test sets were resized to 50 x 1000 pixels and number of states in the model was fixed at 50% of maximum possible overlapping states of the image. Table 1 shows the accuracy of HMMBW, HMMMLP and HMMCNN model for various train and test cases. Like HMMBW model, number of samples in train set was varied from 1 to 6 and remaining images of the writer are considered in the test set. Total number of train samples and test samples are also shown in Table 1 as the number samples per writer varies.

It can be observed from Table 1 that HMMMLP and HMMCNN have yielded better results than that of HMMBW. HMMBW is the model in which Baum-Welch algorithm was used to determine the optimal transition and emission matrices. Performance of HMMBW is already discussed in Chapter V. The performance of HMMCNN is better than HMMMLMP in all the training sets.

Table 1: Variation in Accuracy of HMMBW, HMMMLP and HMMCNN with Sample Size

Number of Samples per writer	Total number of training samples	Total number of test samples	Ratio of test to train set	Total Matches	Total Mismatches	HMMBW Accuracy	HMMMLP Accuracy	HMMCNN Accuracy
1	100	780	7.80	130	650	16.67%	20.50%	22.35%
2	200	680	3.40	280	400	41.18%	46.25%	50.15%
3	300	580	1.93	300	280	51.72%	57.00%	59.50%
4	400	480	1.20	300	180	62.50%	66.30%	68.10%
5	500	380	0.76	270	110	71.05%	74.40%	79.80%
6	600	280	0.47	270	10	96.43%	97.30%	98.50%

Accuracy of HMMMLP and HMMCNN increase with increase in sample size in training set. Accuracy is measured on the test set. The train set was sampled 5 times and model was trained 5 times. Accuracy shown in Table 1 is the average accuracy on test sets of different samples of 5 models. Accuracy of HMMCNN models are better than that of HMMMLP by at least 1%. As explained in previous chapter, ratio of test to train set at 0.47, that is when train set is nearly 70% of total size, the accuracy is maximum at 97.3% and 98.5% respectively for HMMMLP and HMMCNN models.

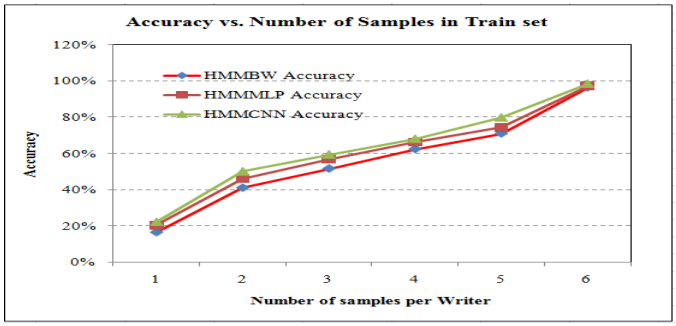

Fig. 3: Variation in Accuracy of HMMMLP and HMMCNN with Sample Size

Fig. 3 shows the pictorial representation of the change in accuracy of HMMBW, HMMMLP and HMMCNN models with respect to change in sample size per writer. Accuracy change is significant when the sample size increase from 5 to 6. As mentioned in previous section, simulations were performed with number of states is equal to 50% of the maximum possible overlapping states of the image in the horizontal direction. In subsequent section, the number of states with respect to maximum possible overlapping states of the image is varied to further improve the accuracy of HMMMLP and HMMCNN.

In Fig. 4, change in accuracy is plotted against the test to train ratio. As the ratio increases, the number of images in test set increases at the cost of train set. Hence number of images in train set decreases with increase in test to train ratio. As the number of images in train set decreases, variation in the data also decreases. Test set will have more variation in data than train set and hence accuracy of all the models decreases. Ideally, train set must capture more variation than that of test set.

Fig. 4: Variation in Accuracy of HMMMLP and HMMCNN with test-train ratio

It was simulated for HMMBW to determine the number states required to achieve maximum possible accuracy. A similar experiment was conducted for HMMMLP and HMMCNN as well. Number of states was fixed at 50% of the maximum possible overlapping states in MLP and CNN in the simulation results presented in Fig. 3. Since CNN requires the input in two dimensional form, states are defined in both horizontal and vertical direction. Maximum number of possible states for HMMMLP is similar to HMMBW since both the models have one dimensional states in HMM. But in case of CNN, there are states in two dimensional form and hence maximum number of possible states are calculated as given below.

Let
W = Width of the image in pixels
H = Height of image in pixels
F = Width of block of each state
G = Height of block of each state
S = Number of strides(one in this case)
Therefore number of overlapping states in horizontal direction (N) = (W – F)/(S) + 1
Therefore number of overlapping states in vertical direction (M) = (H – G)/(S) + 1
For an image width (W) of 1000 pixels, if the stride (S) is 1 and for block width (F) of 50,

Number of overlapping states in horizontal direction (N)
= (1000 – 50)/1 + 1 = 951
Similarly, for an image width (H) of 50 pixels, if the stride (S) is 1 and for block height (G) of 10,
Number of overlapping states in vertical direction (M)
= (50 – 10)/1 + 1 = 41
Maximum ratio of states to Width = [N x M] / [W x H]
= [(W – F)/(S) + 1] x [(H – G)/(S) + 1] / [W x H]
= [951 x 41] / [1000 x 50]
= 77.9% (~80%)

Now for a given ratio of states to product of width and height, it is possible to calculate the number of states. Also it I possible to calculate the strides for a given W, H, F and G when N and M are known.

The number of states is expressed as percentage of maximum possible overlapping states to determine the best achievable accuracy. In case of HMMBW and HMMMLP, maximum possible states are 95.1% of W. In case of CNN, it is 77.9% of product of width and height. The plot shown in Fig. 5 depicts the variation in accuracy as the % of maximum possible number of overlapping states is varied.

Table 2: Variation in Accuracy of HMMMLP and HMMCNN with number of states

Number of states as percentage of width	HMMBW Accuracy	HMMMLP Accuracy	HMMCNN Accuracy
50%	96.43%	97.30%	98.50%
60%	96.90%	97.40%	98.50%
70%	97.60%	97.90%	98.60%
80%	98.10%	98.10%	98.75%
90%	99.20%	99.50%	99.85%
91%	99.90%	99.70%	99.90%
92%	99.30%	99.95%	99.95%
93%	99.10%	99.90%	99.85%
94%	98.90%	99.10%	99.20%
95%	98.90%	99.00%	99.10%
100%	98.40%	98.60%	99%

It can be observed in Table 2 and Fig. 5 that as the number of states is increased, accuracy has increased in case of HMMMLP from 97.3% to a maximum of 99.95%. Maximum accuracy is obtained when number of states was at 92% of the maximum possible overlapping states. When the number of states was increased to 93%, though the accuracy was reasonably close to maximum accuracy, it dropped by 0.05%. The accuracies are averaged on 5 different samples drawn from VTU-WRITER dataset. Accuracy drops 98.6% when all possible states were used in the model. Hence having more number of states also is not a solution to improve the accuracy. The optimal number of states for the best accuracy is dependent on the train and test datasets. The experiments were conducted for a test-train ratio of 0.47.

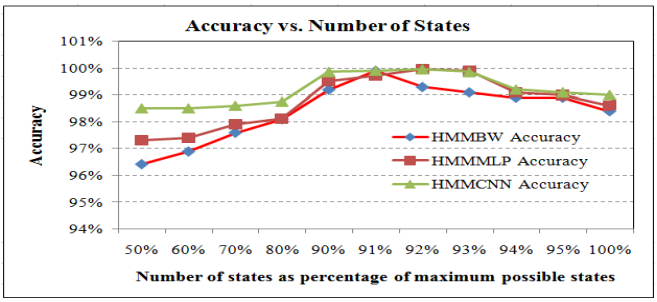

Fig. 5: Variation in Accuracy of HMMBW with number of states (% of maximum possible overlapping states)

Similarly for HMMCNN model, highest accuracy was obtained when 92% of the states (92% of 77.9% of product of width and height) were used in the model and the accuracy was at 99.95%. Accuracy again falls when the number of states was increased beyond 92%. One observation can be made regarding HMMMLP and HMMCNN in this regard. Both the model yielded an accuracy of 99.95% at 92% of the states. But from Fig. 5, it can be observed that HMMCNN has performed better than HMMMLP or HMMBW overall in all simulations when number of states were varied from 50% to 100%. Hence HMMCNN can be treated as the best among all the three models.

IV. CONCLUSIONS

In this work writer identification was performed with three hybrid methods. In the hybrid methods, features are extracted using HMM and optimization and classification is performed using Baum-Welch, MLP and CNN models. The MLP and CNN has feature extraction again in the model in addition to the HMM. Hence with the HMMMLP and HMMCNN, there are two stages of feature extractions. Accuracies of HMMBW, HMMMLP and HMMCNN are verified and compared for VTU-WRITER dataset. It has been found that HMMBW yielding 99.9% accuracy, HMMMLP and HMMCNN yielding 99.95% accuracy. But the this accuracy was possible only when the number of states were defined as 91%, 92% and 92% for HMMBW, HMMMLP and HMMCNN respectively.

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